Texture Discrimination using a Flexible Tactile Sensor Array on a Soft Biomimetic Finger

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***Abstract*— Soft robotic fingers provide enhanced flexibility and dexterity when interacting with the environment. The capability of soft fingers can be further improved by integrating them with tactile sensors to discriminate various textured surfaces. In this work, a flexible 3x3 fabric-based tactile sensor array was integrated with a soft, biomimetic finger for a texture discrimination task. The finger palpated seven different textured plates and the corresponding tactile response was converted into neuromorphic spiking patterns, mimicking the firing pattern of mechanoreceptors in the skin. Spike-based feature metrics were used to classify different textures using the support vector machine (SVM) classifier. The sensor was able to achieve an accuracy of 99.21% when two features, mean spike rate and average inter-spike interval, from each taxel were used as inputs into the classifier. The experiment showed that an inexpensive, soft, biomimetic finger combined with the flexible tactile sensor array can potentially help users perceive their environment better.**

Keywords—Soft biomimetic finger; Flexible tactile sensor array; Neuromorphic model; Supervised learning.

I. Introduction

Soft robotic devices have become increasingly popular in fields such as surgical robotics, prostheses due to their biomimetic capabilities. Soft robots are commonly fabricated from non-traditional materials such as silicone and are activated via pneumatic, hydraulic, or polymeric methods. The compliant nature of soft robots allows them to conform to objects and safely interact with their environment [1]. Additionally, soft actuators provide many degrees of freedom and large ranges of motion without adding components or response time [2]-[4]. While it has been reported that soft robotic devices have been able to detect static information like temperature, curvature, and force [5]-[7], the detection of dynamic cues such as texture has not been thoroughly explored.

Dynamic cues are detected using active palpation by moving a tactile sensor (Fig. 1) over a textured surface. The texture is perceived by determining the changes in shape, size, and pliancy of the surface over time. The sensation of texture allows users to better perceive and interact with objects in their surroundings [8], [9]. In minimally invasive surgery, robots have been using texture to identify tumors and abscesses [10]. Texture discrimination also provides tactile feedback such as compliance to a prosthesis user to more dexterously manipulate everyday objects [11], [12]. There has been a previous study which integrated a single tactile sensor with a soft biomimetic finger with promising results [13], but a tactile sensor array has yet to be integrated. Multiple sensors on a soft finger could create a more realistic sensation for the user. The fabrication of a biomimetic prosthesis would not only require physical components such as a soft materials and tactile sensors, but more organic signal processing as well. This can be accomplished through neuromorphic encoding and classifiers.

Neuromorphic encoding is a process where tactile information from sensors is transformed into spike patterns, mimicking neural signals produced by mechanoreceptors in the human skin. This work uses the Izhikevich framework's slowly adapting neuron model to create spike trains, which vary in frequency in response to input amplitude. Neuromorphic encoding allows for efficient relay of feedback information which can seamlessly integrate with biological systems [14]. After the texture information is translated into spiking patterns, supervised machine learning algorithm, support vector machine (SVM), is used to classify the textures.

In this study, we present a soft biomimetic finger integrated with a 3x3 flexible tactile sensor array capable of texture discrimination using neuromorphic encoding and supervised learning.

II. Materials

A. Sensor Design

The 3x3 fabric-based tactile sensor array (Fig. 1) is a variation of a previous multilayer sensor design [15]. This sensor array with 9 taxels, or sensing elements, is small enough to be integrated with the soft biomimetic fingertip. Each taxel has a sensing area of 2x2 mm^2 spaced at 2.5 mm intervals. The piezoresistive fabric transforms the applied force into changes in voltage [18]. The sensor voltage output was measured in a voltage divider by connecting the sensor in series with a 10 kΩ resistor.

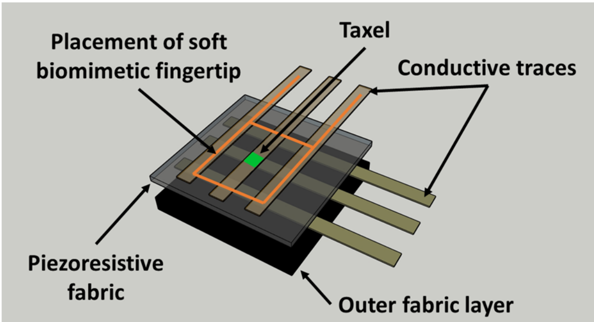

Fig. 1. Graphic overview of the 3x3 flexible tactile sensor array. The perpendicular crossing 2 mm strips of conductive traces sandwich the piezoresistive fabric to create 2x2 mm^2 taxels (sensing element) spaced 2.5 mm apart. The sensor is integrated with the soft biomimetic finger.

B. Soft Biomimetic Finger

The soft biomimetic finger (Fig. 2) has the same design as a previous finger [13] but with a different integrated sensor. To mimic the trajectory of the human finger, the soft biomimetic finger has three joints, metacarpophalangeal (MCP), proximal interphalangeal (PIP), and distal interphalangeal (DIP). The pneumatically actuated finger has two degrees of freedom, with the MCP joint being actuated independently from the PIP and DIP joints, which share the same pneumatic channel.

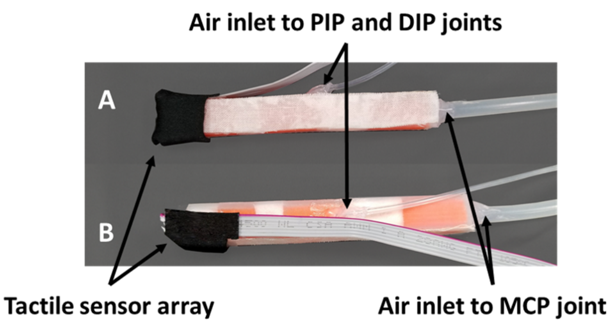

Fig. 2. Soft finger integrated with the tactile sensor array. (A) Bottom view; (B) Side view. The orange sections form the joints.

The silicone rubber Dragon Skin™ 10 Medium (Smooth-On, Macungie, PA, USA) composes much of the soft finger with orange cotton fiber wound twice around the inner layer to prevent radial expansion. Strips of white cotton fabric were also wrapped around certain parts of the finger to mimic the joints of the human finger. The areas without the strain limiting fabric, become the MCP, PIP, and DIP joints. On the outer layer of silicone, an additional layer of white cotton fabric was adhered to the palmar surface of the finger to create the directional curvature that mimics the human finger.

C. Textured Plates Design

To test the sensor for texture discrimination, 7 textured plates with varying textures were designed (Fig. 3). The 36x36 mm^2 textured surfaces with 2.5 mm raised ridges and bumps were centered on a 108x36 mm^2 plate. An isolated textured surface for palpation was created by including flat surfaces on either side.

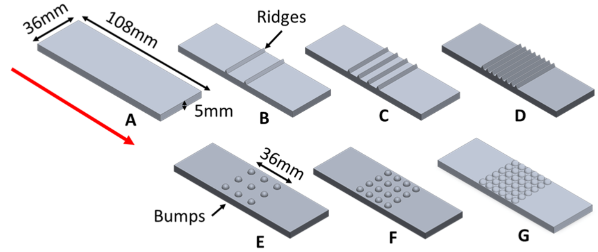

Fig. 3. Textured plates designed for testing texture discrimination. (A) Flat; (B) 2 ridges; (C) 4 ridges; (D) 8 ridges; (E) 3x3 bumps; (F) 4x4 bumps; (G) 6x6 bumps. The red arrow indicates the direction of palpation.

III. Methods

A. Experimental Procedure

The soft biomimetic finger was mounted on the UR5 Robot arm (Universal Robots, Odense, Denmark) to palpate the textured plates (Fig. 4). The soft finger was used to in its uninflated state. First, the finger was brought down to one side of the textured plate until the sensor array made physical contact. Then, the texture was palpated by moving the entire finger horizontally along the direction of palpation, shown in (Fig. 3). Each texture was palpated at approximately 60 mm/s with 32 repetitions. The output of each taxel was sampled at 100 Hz by the Arduino Mega 2560 microcontroller and processed in MATLAB.

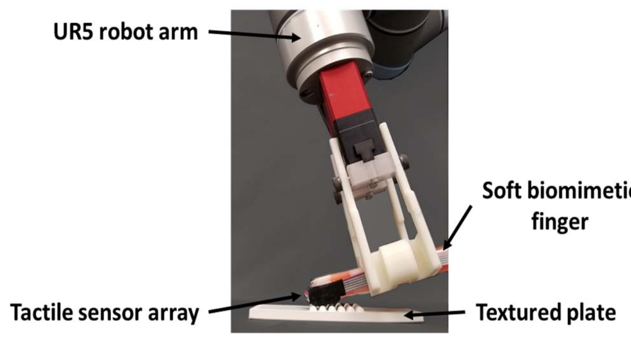

Fig. 4. Overview of the experimental setup with the soft biomimetic finger integrated with the tactile sensor array mounted on the UR5 arm palpating the textured plates.

B. Neuromorphic Encoding

To mimic mechanoreceptor activity, the tactile response from each taxel of the tactile sensor was converted into slowly adapting (SA-1) neuron spiking patterns using the Izhikevich neuron model [19]. This approach has been used previously for similar applications [13], [16], [17], [20], [21]. The Izhikevich neuron model uses (1), (2), and (3) equations to produce the spike train with recovery variable *u,* membrane voltage *v*, and injected current *I* [19].

$$\frac{dv}{dt} = 0.04v^2 + 5v + 140 - u + kI \quad (1)$$

$$\frac{du}{dt} = a(bv - u) \quad (2)$$

$$if\ v \geq 30\ mv, then \begin{cases} v \leftarrow c \\ u \leftarrow u + d \end{cases} \quad (3)$$

To mimic SA-1 neurons, the Izhikevich model parameters were a = 0.02, b = 0.2, c = -65, and d = 8. The voltage output of the taxels were normalized and a gain factor, *k*, of 15 was applied before serving as the input current for the neuron model.

The sensor array's responses for each of the textures were collected and segmented into 9 s windows, based on the duration of each trial, before being converted into spike trains offline using MATLAB. Then, to compress the information for the classification algorithms, the mean spike rate and average inter-spike interval were calculated for each trial. The mean spike rate was calculated by counting the number of spikes within 100 ms bins and dividing it by the bin length for each trial. The average inter-spike interval was calculated by averaging the time elapsed between each spike in the window.

C. *Classification Algorithms*

To test the ability of the sensor array to discriminate between the textures, two features from each taxel for each trial were used as inputs for the classifier. The two features being mean spike rate and average inter-spike interval. This resulted in 18 features, 2 per taxel, becoming the input for the classifier. Of the 32 trials from each textured plate, 24 trials were randomly selected for the training set and the remaining samples were used as the testing set. This process was repeated 1000 times to reduce the training set bias.

A supervised learning algorithm was used for texture classification because the identities of the textures are known. The linear kernel of SVM was implemented in MATLAB because it did not require the assumptions of normal distribution and similar within-class variance. Additionally, SVM had been shown to discriminate textures well in previous studies [16].

IV. Results and Discussion

A. *Neuromorphic encoding*

The spiking patterns (Fig. 5) were generated by the neuron model of a single taxel when palpating textures B and E. Texture B had constant spiking when the normalized voltage was high, while texture E had more gradual changes in amplitude and resulted in fewer spikes around the edges of the bumps.

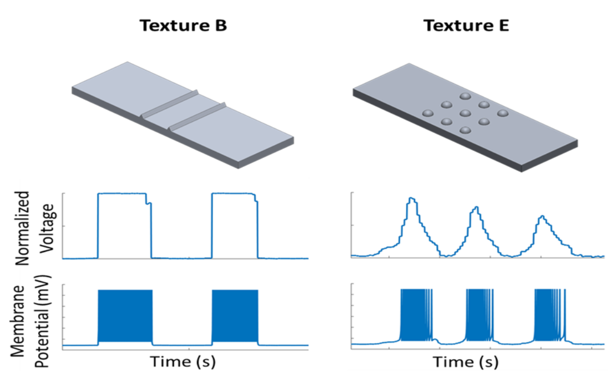

Fig. 5. Overview of the neuron spiking response for Textures B & E based on the input voltage from a single taxel on the tactile sensor.

B. *Classification Accuracy*

The classification results presented in (Fig. 6), showed the 3x3 tactile sensor was able to reliably discriminate between seven textures when compressed neuromorphically encoded features were run through the SVM classifier. The sensor was able to achieve an overall 99.21% classification accuracy using SVM, with every texture being reliably classified (>96% accuracy). When the two features from individual taxels on the sensor were used separately as inputs for the classifier, the overall accuracy ranged from 54.01% to 92.86%. Due to the spatial integration of all the taxels on the sensor, a higher total classification accuracy was achieved. At almost complete accuracy over seven textures, this fingertip sensor array, with an increased spatial resolution, shows promise for robust texture discrimination for soft robotics.

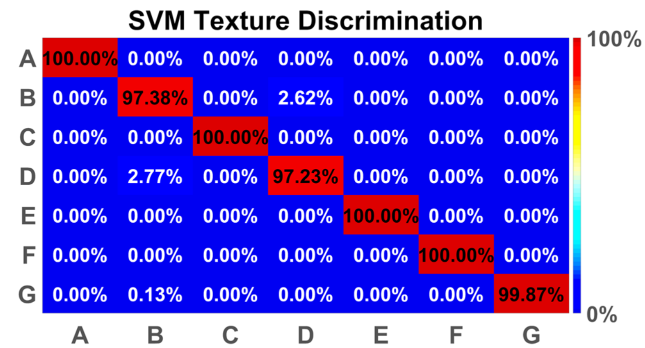

Fig. 6. Texture classification results showing the SVM algoritm's accuracy for classifying each of the textures from Fig. 3. Overall, the sensor was able to reliably discriminate between the textures with SVM achieving 99.21% overall classification accuracy.

V. Conclusion

We showed that a 3x3 flexible tactile sensor array integrated with a soft biomimetic finger can discriminate textures through palpation. The compressed neuromorphic representation of the tactile response was used to classify the textures. This work combines the aspects of previous work [13], [16], [17] to improve texture discrimination with an increased number of taxels on the soft biomimetic finger to achieve more spatial information in addition to a more robust classifier.

Validation of this approach with a larger texture database and understanding the varying levels of actuation of the soft biomimetic finger during palpation needs further investigation. To palpate finer textures, the higher spatial resolution tactile sensor would be beneficial. In conclusion, results of this study indicate that soft biomimetic fingers with tactile sensing ability have potential to reduce the gap between a healthy arm and prosthesis by allowing users to improve their sense of touch while perceiving and interacting with their environment.

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